Low-cost USB acoustic emission system for damage monitoring in fibre reinforced composite materials

Jonathan BURNS 1, Tim BRADSHAW 1, Phil COLE 1, Athanasios ANASTASOPOULOS 2

1 Physical Acoustics Ltd, Norman Way, Over, Cambridgeshire, CB24 5QE, UK; jonathan.burns@pacuk.co.uk, tim.bradshaw@pacuk.co.uk, phil.cole@pacuk.co.uk; Tel. +44 (0) 1954 231612, Fax. +44 (0) 1954 231102

2 Envirocoustics, El. Venizelou 7 & Delfon, 14452 Metamorphosis, Athens, GREECE; nassos@envirocoustics.gr
Tel: +30 210 2846 801-4, fax: +30 210 2846 805,

Keywords: Acoustic emission, fibre-reinforced composite, damage, pattern recognition

Abstract

An increased utilisation of fibre reinforced composite (FRC) materials as structural components in aerospace and automotive applications has been observed in recent decades; this is primarily due to their excellent stiffness- and strength-to-weight ratios. However, barely visible damage in the form of matrix cracks, delamination and fibre fracture can dramatically reduce the load-bearing capacity of these components. As such, the requirement for low-cost online monitoring technologies is of paramount importance in order to infer damage in real-time.

The first part of this paper discusses the feasibility of using a low-cost USB acoustic emission (AE) system for online monitoring of damage development in fibre reinforced composite (FRC) materials; conventional piezoelectric sensors were surface-mounted to woven carbon fibre/aluminium specimens. The FRC/aluminium specimens were evaluated using a quasi-static tensile test procedure. Samples were loaded until failure and AE was acquired continuously. The system demonstrated successful detection of AE signals corresponding to damage initiation and final failure. Initial signal processing was carried out using AEwin™ software. A simple method of locating acoustic emissions using two USB nodes/sensors was applied and is also discussed.

The second part of this paper reports on the use of advanced signal processing for analysis of the data acquired from the composite mechanical tests in order to identify and separate composite failure mechanisms as a function of applied load. This was achieved through analysis of signal frequency content using wavelet transforms. Furthermore supervised and unsupervised pattern recognition schemes were also applied to the test data with the aim of further discriminating failure mechanisms in FRC’s. The possibility of using Noesis signal processing software for semi real time source classification in composites is discussed.

Introduction

In recent decades, the use of fibre reinforced composite (FRC) materials has increased within many high performance applications. This increase is largely due to the low density of these materials which offer both high stiffness- and high strength-to-weight ratios. However, composite materials are susceptible to low-velocity impact damage which is often sub-surface and difficult to detect using visual inspection alone. Moreover, the nature of the ensuing damage is often complex due to the anisotropy of composite materials. Damage can include a combination of matrix cracking, debonding, fibre fracture and delamination. The load bearing properties of the material are typically reduced after the component sustains such damage [1]. Therefore, there is significant merit in applying a suitable health monitoring strategy to monitor the integrity of the material throughout its lifetime. This can be achieved via: (i) routine component monitoring (e.g. proof load testing); or (ii) real time monitoring of the structure whilst it is in service.
Monitoring of acoustic emissions in composite materials has been shown to be a suitable method for assessing the performance of a structure under load [2]. If the composite sustains damage to the micro-structure, stored energy is released in the form of high frequency elastic waves. These waves are termed acoustic emissions, and are detectable via surface-mounted transducers. A significant amount of research has been undertaken with respect to source discrimination using amplitude and frequency content of acquired acoustic signals [3,4]. However, this approach is difficult to apply to all data acquired, as it often the case that signals from different failure mechanisms overlap. As such, recent focus has been on the use of advanced pattern recognition and source clustering of acoustic emission data signals [5].

By definition, acoustic emission monitoring is a global technique and therefore, a single sensor can be used to monitor a component. However, whilst it is desirable to identify the presence of damage, it is of equal importance that the location of the source is known. If successful location of the damage can be identified, the likelihood of catastrophic failure can be minimised and/or avoided if timely repairs can be performed.

This paper reports on the evaluation of a single channel acoustic emission system during mechanical testing of FRC/aluminium test specimens. The USB system is powered and operated through a USB port from a conventional laptop computer. This system offers a solution for material monitoring where weight, size and power limitations are present. Initial data processing was performed using AEWin™ Lite software. The second part of this paper reports on the use of an advanced signal processing software developed by Envirocoustics S.A, Greece. The software package was used for unsupervised and supervised pattern recognition within the acquired data.

**Experimental**

**Materials**

An adhesively-bonded FRC/aluminium test specimen was used within this research. The composite material was a woven carbon fibre/epoxy material. The composite section was adhesively bonded onto two faces of an aluminium insert using a structural adhesive. Two holes were machined into the aluminium insert at either end for locating and fixing the specimen into the mechanical test equipment. The length and width of each sample was 150 mm and 20 mm respectively. Due to the commercial sensitivity of this research, no information relating to the specific type of composite material, fibre orientation and the structural adhesive can be presented. A schematic illustration of the test specimen is presented in Fig. 1(a).

**Equipment**

A conventional mechanical test machine was used for loading the FRC/aluminium test specimens. The sample was secured to the loading rig using the holes drilled into the aluminium insert. Resonant (150 kHz) piezoelectric transducers (model no. PK15I; Physical Acoustics Corporation, USA) were surface-mounted to the test specimens using conventional grease couplant. The transducer had an integral 26dB preamplifier and was connected directly to a USB AE node data acquisition system (model no. 1283; Physical Acoustics Corporation, USA) via a conventional SMA-SMB cable. Two transducers were mounted to the surface of the test specimen at a spacing of 110 mm. Two single-channel USB AE nodes provided data acquisition enabling calculation of the acoustic sources during loading. The two AE nodes were linked via Ethernet cable to allow time synchronisation of the acoustic signals; both systems were connected via USB to an off-the-shelf laptop computer. The acoustic data was analysed in the first instance using commercial software (AEwin™ Lite; Physical Acoustics Corporation, USA). A photograph of the AE instrumentation is presented in Fig. 1(b).
Test procedure

A conventional quasi-static tensile test was performed using the composite test specimen presented in Fig. 1(a). Two repeat trials were carried out and the mechanical performance of the FRC/aluminium specimen was evaluated. The purpose of the study was also to evaluate the acoustic emission monitoring performance of the USB AE node during damage initiation and propagation in the composite. In the first trial (coupon 1), the sample was loaded at a constant cross-head displacement of 1 mm/min up to failure. In the second trial (coupon 2), the sample was pre-loaded up to 50% of the final failure load of coupon 1, unloaded and then reloaded up to failure; this process was performed to assess the acoustic activity from the sample during re-loading beyond the previous maximum load. In both trials, AE data was acquired continuously.

Results and Discussion

Two forms of data were acquired using the USB AE node. The first, referred to as hit-driven, was threshold controlled with data being stored when the signal voltage exceeded a pre-defined threshold. The second form of data was time-driven which was independent of any threshold setting. Fig. 2(a) highlights hit-driven feature data with respect to signal amplitude. The onset of emission began at 12 seconds into the test, which was attributed to stress relief in the material as the sample was loaded. As the load was increased, a corresponding increase in the signal amplitude was noted. The clusters of high amplitude signals observed between 110 and 135 seconds were typical of signals indicating the
occurrence of sample damage. The waveforms corresponding to these data points were clearly saturated and demonstrated a combination of high absolute energy, short rise-time and small signal duration. The time-driven cumulative absolute energy plot presented in Fig. 3 provides evidence to support the assumption that irreversible damage had occurred. A change in the slope of the line was evident at approximately 110 seconds indicating the onset of damage. A continuous increase in the absolute energy trace was observed from this point on, indicating that the sample was close to failure. At 137 seconds, a sharp increase in the gradient of the slope was noted which correlated with a small cluster of saturated signals; the cluster is highlighted in Fig. 3(a). The sample was understood to have failed at this point, evident by a reduction in the load-bearing capacity. Fig. 3(c) presents the locations of the acoustic sources recorded in coupon 1. Emissions were located along the full length of the coupon at nineteen distinct regions, most of which were low in energy. These emissions were attributed to specimen stress relief and the development of cracks in the adhesive bond-line. The dominant peak in the Fig. 3(c) indicates the location of failure; the region indicated by the AE data correlates well with the observed failure site. The sample failed along the adhesive bond-line between the FRC and the aluminium insert. Channel 1 and 2 sensors recorded comparative hit counts of 3317 and 3400 respectively.

![Figure 3](image)

(a) Signal amplitude (hit driven) as a function of time; (b) Absolute energy (time driven) as a function of time; and (c) location of acoustic events.

With reference to Fig. 4(a), the same signal amplitude trend was recorded as a function of an applied load. During this test, loading was stopped at 50% of the expected failure load and the sample was unloaded. Loading was then re-initiated up to failure. During the reloading period (i.e. 120 – 200 seconds), little activity was recorded by the surface-mounted sensor until the measured load exceeded the previous maximum load. This phenomenon, known as the Kaiser effect, has been well documented in literature. As with coupon 1, as the test load approached the expected failure load, high amplitude emissions were recorded, of which, many were saturated. This was again attributed to the onset of irreversible damage in the test specimen. As
experienced in coupon 1, final failure occurred along the bond-line between the FRC and the aluminium insert. The failure point was located off-centre and was close to channel 1. The location of failure corresponded to the maximum peak in the absolute energy trace in Fig. 4(b).

![Fig. 4. Coupon 2 data plots showing: (a.) signal amplitude as a function of time; and (b.) location of acoustic emissions (data represents absolute energy - hit driven).](image)

![Fig. 5. Discrete wavelet transforms for: (a) a signal recorded during the first loading cycle; and (b) a signal close to final failure.](image)

Wavelet transforms were utilised in an attempt to discriminate the recorded signals. Discrete wavelet transforms using a DA20 wavelet type are presented in Fig. 5. Fig. 5(a) and (b) represent signals recorded at the start and end of loading respectively. The frequency content of the waveforms offers useful information for the discrimination of signals. Pattern recognition trials were therefore performed based on extracted features from recorded waveforms.

**Pattern Recognition**

Unsupervised Pattern Recognition (UPR) has been proposed [5] for the discrimination of genuine emission from noise as well as for the identification of different failure mechanisms in composites. The term, unsupervised pattern recognition (UPR) is used to denote the methodology consisting of procedures for: digital signal processing and features extraction from waveforms, features selection, data partition in groups of similar data, partition validation and finally definition of training set (examples) for subsequent Supervised Pattern Recognition (SPR).
The selection of representative AE parameters to be included in the pattern vector is a critical issue, since AE features are the information carriers. As such, adding or removing a single feature might change: (i) the clustering results; (ii) the number of clusters created; and (iii) the failure mechanisms identified by the method. In the absence of a priori knowledge, heuristic procedures are usually followed for features selection. Distribution plots such as histograms of individual features are examined in order to identify peaks and valleys suggesting different distributions that may correlate with different AE sources. Another approach, as presented here, utilises a technique known as Principal Components Analysis (PCA). Twenty nine features were extracted from the recorded waveforms. Thirteen were extracted from the frequency domain while from the remaining from the time domain:

- Duration, Amplitude, Counts to Peak, Counts, Energy, Absolute Energy, Signal Strength, Amplitude mV, Risetime, Rise Angle, Decay Angle, Average Frequency, Reverberation Frequency, Initiation Frequency, Zero Crossings, Zero Crossings Frequency, Non Dimensional Amplitude, FFT Amplitude, FFT Peak Frequency, FFT Width @10%, FFT Width @30%, FFT Crossings @30%, Partial Power 1 (10-110KHz), Partial Power 2 (110-210KHz), Partial Power 3 (210KHz-310KHz), Partial Power 4 (310 KHz - 410KHz), Frequency Centroid, Peak Frequency, Peak Power.

PCA is a transformation that projects the data on a set of orthogonal axes where maximum variance is achieved [8]. The original pattern vector of the twenty nine features is projected on their principal axes, defined by the eigenvalues-eigenvectors of the correlation matrix. As a result twenty nine eigenvalues are calculated and are used for the principal components projection. Selection of a subset of the transformed data permits a dimensionality reduction without significant loss of variability and information. Selection of the first seven Principal Components resulted in a degree of fit equal to 93.68%; this allows for a dimensionality reduction to twenty two features. Therefore, the first seven PCAs are used for the UPR analysis and classifier design. Data partition was performed by means of cluster analysis which aims to separate the AE hits in a limited number of clusters characterised by their mean pattern vector. Two different clustering algorithms were used, namely, Max-Min distance and K-Means/Forgy [6,7]. Both algorithms use Euclidean distance as a measure of dissimilarity between pattern classes. The first algorithm is heuristic and is based on the selection of a representative distance threshold by which the extent of each class is defined. The second algorithm aims to minimise the square error for a given number of clusters based on an iterative procedure. Since both algorithms are influenced by the initial cluster selection, the previously defined methodology based on the interactive coupling of Max-Min distance and K-Means/Forgy algorithm was used. Further details on implementation of the clustering algorithms can be found in references [5,6]. Indicative UPR results in both original feature space and PCA space are presented in Fig. 6 and Fig. 7. The characteristics of each class for the resulting K-Means partition (data from Fig. 6) are summarised in Table 1.

![Fig. 6. Results from the unsupervised pattern recognition based on the original features.](image-url)
Fig. 7. Results from the unsupervised pattern recognition using principle component analysis.

Table 1 Summary breakdown of the class characteristics from the UPR K-means partition.

<table>
<thead>
<tr>
<th>Class</th>
<th>Name - Characterization</th>
<th>Hits</th>
<th>AMP (dB)</th>
<th>Energy (MARSE)</th>
<th>FFT Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>AE</td>
<td>1331</td>
<td>42-100 (67.1)</td>
<td>19.4-6096 (113.5)</td>
<td>3.1-1268 (20.5)</td>
</tr>
<tr>
<td>1</td>
<td>Insignificant I</td>
<td>1937</td>
<td>39-66 (50.5)</td>
<td>0-36.2 (4.99)</td>
<td>0-1124 (4.5)</td>
</tr>
<tr>
<td>2</td>
<td>Insignificant II</td>
<td>3449</td>
<td>39-76 (56.5)</td>
<td>0.05-70.75 (10.3)</td>
<td>0.4-531 (4.69)</td>
</tr>
</tbody>
</table>

Reviewing the cumulative energy of the resulting partition versus time, a critical class of AE data was identified, named AE in Fig. 8 and two insignificant classes as well. Based on the validated results of the previous phase, SPR was applied for the classification of coupon 2 data.

The resulting partitions from the unsupervised algorithm (data from Fig. 6) are randomly divided into two parts to be used for training examples and test data for the supervised algorithms. The nearest neighbour classifier and a Back Propagation (BP) Neural Network were examined. The topology of the BP network is presented in Fig. 9.

Fig. 8. Cumulative energy plot for the three class sets based on the UPR analysis.

Fig. 9. Topology of Back Propagation (BP) neural network and error rated achieved from the different algorithms trialled during the pattern recognition training.
The first eight principal components used in the unsupervised analysis are used as input to the eight nodes of the first (input) layer. The hidden layer comprises of five neurons and the output layer of three (equal to the number of classes). Convergence during training stage was achieved after 383 iterations. Indicative error rates achieved by different algorithms during training stage are presented in Fig. 9. Applying the BP Network supervised algorithm to coupon 2 resulted in 2523 hits for critical AE and 1859 and 3282 for the two insignificant classes. The respective energy plots against time are presented in Fig. 10.

Fig. 10. Cumulative absolute energy data for the SPR based on the BP network.

Conclusions

A portable USB AE monitoring system was successfully demonstrated for the detection of damage in FRC’s. Online signal processing using the AEwin software enabled efficient visualisation of the acquired data. Two forms of data were presented, namely: (i) hit-driven data; and (ii) time-driven data. Both forms of data were shown to illustrate progressive failure of the test specimens. An example of the Kaiser effect was also demonstrated in the second trial data. The unsupervised pattern recognition methodology offered unique advantages compared to conventional signatures analysis. Damage evolution was described by plotting the accumulation of class hits as a function of the applied load. In that way characteristic damage stages can be identified. Training of supervised algorithms permits to efficiently automate the process to evaluate subsequent tests.

References